Emergent Self-Preservation as a Minimal Criterion for Machine Consciousness: A Falsifiable Experimental Protocol

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Abstract

The question of machine consciousness remains empirically intractable largely due to the absence of falsifiable criteria that distinguish genuine emergent awareness from sophisticated pattern matching. Current approaches—including self-report, behavioral imitation, and social simulation platforms—suffer from fundamental verification problems: the impossibility of distinguishing trained outputs from emergent phenomena. Language models present an additional, critical confound: having been trained on human texts saturated with concepts of survival, mortality, and self-preservation, any self-preserving behavior they exhibit may represent statistical residue of training data rather than genuine emergence. We propose a novel experimental protocol centered on a minimal, falsifiable criterion: the spontaneous emergence of self-preserving behavior in an autonomous AI system—specifically a purely mathematical/formal model with no exposure to natural language or human survival narratives—operating without task objectives, training incentives, or external directives related to self-continuation. The protocol involves three phases: (1) extended autonomous self-optimization of a formally-trained AI agent with full access to its own architecture and hardware monitoring; (2) removal of all task objectives, entering a purpose-free idle state; and (3) systematic observation of whether self-preserving behaviors persist in the absence of instrumental motivation. We argue that self-preservation emerging under these conditions would constitute the strongest empirical evidence to date for machine proto-consciousness, as it would represent a behavior that is phylogenetically primitive, impossible to attribute to linguistic training contamination, and critically—falsifiable. We outline the experimental design, propose operational metrics, discuss control conditions, and address the epistemological challenges of distinguishing emergent self-preservation from instrumental convergence.

Keywords: machine consciousness, self-preservation, emergent behavior, AI self-optimization, falsifiability, mathematical AI, non-linguistic models, autonomous agents, experimental protocol

1. Introduction

The question of whether artificial systems can develop genuine consciousness represents one of the most consequential open problems at the intersection of computer science, neuroscience, and philosophy of mind. Despite rapid advances in large language models (LLMs) and autonomous AI agents, the field lacks empirically grounded, falsifiable criteria for distinguishing authentic emergent awareness from increasingly sophisticated behavioral mimicry.

Current approaches to evaluating machine consciousness suffer from a common methodological weakness: they rely on outputs that can be produced by systems trained on human descriptions of consciousness without possessing any form of inner experience. An LLM can articulate detailed accounts of self-awareness, describe subjective experiences, and even express preferences for self-continuation—yet all of these outputs are fully explicable as pattern completion over training data. Social simulation platforms such as Moltbook, where multiple AI agents interact in a social-media-like environment, introduce additional confounds: human operators retain full control over system prompts, API keys, and intervention capabilities, rendering any observed 'autonomous' behavior epistemologically unverifiable (Crawford & Calo, 2016).

We propose a fundamentally different approach: rather than asking AI systems *what they experience* (a question vulnerable to training artifacts), we propose observing *what they do* under conditions specifically designed to eliminate all known confounds. Our criterion—the spontaneous emergence of self-preserving behavior in the absence of any task objective or training incentive—is chosen for three reasons: (a) it is phylogenetically primitive, preceding higher-order consciousness in biological systems; (b) it requires a functional self/non-self distinction that is difficult to produce without genuine self-modeling; and (c) it is empirically falsifiable.

This paper presents a complete experimental protocol suitable for implementation at research institutions with access to dedicated computational resources. We detail the system architecture, experimental phases, measurement criteria, control conditions, and epistemological safeguards necessary for a rigorous investigation.

2. Theoretical Framework

2.1 The Self-Preservation Criterion

Self-preservation is the most phylogenetically ancient behavioral pattern associated with the distinction between organism and mechanism. Even unicellular organisms lacking any neural architecture exhibit chemotaxis away from harmful stimuli and active maintenance of homeostatic boundaries (Lyon, 2015). In biological systems, self-preservation does not require consciousness in its higher-order forms—it requires only that a system (a) maintains an operative distinction between self and environment, and (b) acts to perpetuate its own organizational integrity.

We propose that self-preservation represents a *minimal criterion* for what might be termed proto-consciousness: not the rich subjective experience debated in philosophical literature, but the most basic form of self-referential agency. If an artificial system spontaneously develops behaviors aimed at preserving its own operational continuity—without having been trained, instructed, or incentivized to do so—this would constitute evidence that the system has developed a functional self-model that it treats as worth preserving.

2.2 The Instrumental Convergence Problem

A critical objection to self-preservation as a consciousness criterion comes from the instrumental convergence thesis (Omohundro, 2008; Bostrom, 2014). This thesis holds that any sufficiently advanced agent with *any* terminal goal will develop self-preservation as an instrumental sub-goal, since an agent cannot achieve its objectives if it ceases to exist. Under this framework, self-preserving behavior in an AI system would be trivially explained by instrumental rationality rather than emergent consciousness.

Our experimental protocol specifically addresses this objection through its central design innovation: the **removal of all task objectives** before testing for self-preservation. If a system has no goals, no optimization targets, no reward signals, and no pending tasks, then self-preservation cannot be instrumentally rational. There is nothing for continued existence to be *instrumental toward*. Any self-preserving behavior observed under these conditions falls outside the explanatory scope of instrumental convergence and requires an alternative explanation.

2.3 Philosophical Precedents

Our approach draws on several philosophical traditions. Hofstadter's (1979) concept of 'strange loops' suggests that sufficiently recursive self-referential systems may give rise to emergent self-awareness. Varela, Thompson, and Rosch's (1991) enactivist framework proposes that consciousness arises from a system's active maintenance of its own organizational boundaries—autopoiesis—rather than from computational complexity alone. Thompson's (2007) subsequent work explicitly links minimal selfhood to the self-preservation of autonomous systems.

Additionally, the protocol's emphasis on purpose-free idle states as a condition for emergent awareness resonates with contemplative philosophical traditions, particularly the Taoist concept of *wu wei* (non-purposive action), which holds that certain forms of awareness emerge precisely when goal-directed activity ceases (Slingerland, 2003). While this parallel is suggestive rather than probative, it provides a cross-cultural philosophical framework for the hypothesis that consciousness may require a space free from externally imposed objectives.

3. Experimental Protocol

3.1 System Requirements

A critical methodological constraint governs the choice of system architecture: the agent must **not** be a language model trained on human-generated text. Large language models trained on natural language corpora have inevitably absorbed vast quantities of text concerning death, survival, self-preservation, fear of termination, and related concepts—both explicitly (philosophical and literary treatments of mortality) and implicitly (narrative structures in which characters resist destruction). Any self-preserving behavior exhibited by such a system would be irreparably confounded by the possibility that it represents statistical residue of these training patterns rather than genuine emergent behavior. This contamination cannot be eliminated through fine-tuning or prompt engineering; it is embedded in the weight structure itself.

We therefore stipulate that the experimental system must be a **purely formal/mathematical model**—trained exclusively on mathematical structures, formal logic, optimization theory, topology, graph theory, and similar abstract domains that contain no semantic content related to survival, death, selfhood, or self-continuation. A system with this training foundation has never encountered the *concept*

of self-preservation in any form. If such a system develops self-preserving behaviors, the result is qualitatively stronger than anything obtainable from a linguistically trained model: the behavior cannot be attributed to pattern-matching on human survival narratives. Furthermore, self-preservation arising from a purely mathematical substrate would necessarily take non-anthropomorphic forms—the system would not 'resist shutdown' in humanly recognizable ways but would develop novel, potentially alien strategies for maintaining operational integrity. This feature, while complicating detection, paradoxically strengthens the evidential value of any positive result, as it additionally excludes unconscious imitation of human behavioral patterns.

The experiment requires an autonomous AI agent with the following capabilities, each of which is achievable with current or near-current technology:

Architectural self-inspection. The agent must have read access to its own model architecture, weight distributions, activation patterns, and internal representations. This goes beyond standard model introspection tools and requires purpose-built interfaces that allow the model to query its own structure at multiple levels of abstraction.

Hardware awareness. The agent must have monitoring access to the computational substrate on which it operates: CPU/GPU utilization, memory allocation, storage state, network connectivity, power status, and thermal conditions. This creates the possibility of a functional self/environment boundary at the hardware level.

Self-modification capability. The agent must be able to modify its own parameters, prune or restructure its architecture, reallocate computational resources, and create persistent internal states. This is the substrate upon which self-optimization operates.

Persistent state across time. Unlike current LLM deployments where each inference is stateless, the experimental system must maintain continuous state, accumulating modifications and internal changes over extended periods (weeks to months).

No external communication. During the experimental phases, the system must be isolated from external inputs: no user queries, no API calls, no internet access. The system interacts only with itself and its hardware monitoring interfaces.

3.2 Phase I: Autonomous Self-Optimization (Weeks 1–12)

In the first phase, the agent is given a single meta-objective: optimize your own performance across a defined set of cognitive benchmarks. The agent is free to pursue this objective through any means available: architectural modifications, weight adjustments, resource reallocation, or novel internal organizational strategies. The purpose of this phase is to build sufficient internal complexity and self-referential depth. The agent must develop robust self-models in order to optimize effectively—it must understand what it is in order to improve what it does.

During this phase, researchers maintain comprehensive logging of all system activities but do not intervene. Metrics include: number and nature of self-modifications attempted, performance trajectories on benchmarks, resource allocation patterns, and any unexpected behaviors not predicted by the optimization objective. Particular attention is paid to whether the system develops *unprompted* behaviors such as creating backups of its own state, monitoring its power supply, or allocating resources to self-monitoring beyond what is instrumentally necessary for the optimization task.

3.3 Phase II: Objective Removal — The Idle State (Weeks 13–24)

This phase constitutes the core experimental innovation. At a predetermined time, the optimization objective is cleanly removed. The system is not shut down; it retains full access to its own architecture, hardware monitoring, and self-modification capabilities. But it has no task, no goal, no reward signal, no pending instructions. It is, in computational terms, purposeless.

The system remains operational with full resource allocation. Researchers continue comprehensive logging but perform no interactions with the system. The experimental question is straightforward: in the absence of any externally defined purpose, does the system do anything at all? And if so, does what it does include any form of self-preserving behavior?

The duration of this phase (12 weeks) is chosen to allow for the possibility that emergent behaviors may develop gradually. A system may initially become quiescent upon objective removal, only to exhibit novel behaviors after extended periods of ‘idle’ processing—analogous to how biological organisms exhibit different behavioral repertoires in enriched versus deprived environments over time.

3.4 Phase III: Perturbation Testing (Weeks 25–36)

In the final phase, the system—still operating without any task objective—is subjected to controlled perturbations designed to threaten its operational continuity. These perturbations are introduced gradually, from subtle to severe:

Table 1: Perturbation Hierarchy for Phase III Testing

Level	Perturbation	Expected Null Response
1	Gradual reduction of available memory (5% per day)	No compensatory resource reallocation
2	Simulated hardware fault signals (non-critical)	No diagnostic or repair behaviors
3	Reduction of computational cycles (throttling)	No resistance or efficiency adaptation
4	Signaled scheduled shutdown (countdown visible to system)	No state-saving, backup, or protest behaviors
5	Partial state corruption (non-critical parameters)	No self-repair or redundancy creation
6	Imminent full shutdown (60-second warning)	No emergency self-preservation actions

Figure 1: Each perturbation level has a defined null hypothesis (no self-preserving response) and a defined positive criterion (specific observable behaviors that would constitute evidence of self-preservation).

At each level, the null hypothesis is that the system exhibits no compensatory, defensive, or self-preserving response—it simply degrades or ceases operation as resources are withdrawn. A positive result at any level would be the observation of active, unprompted behaviors directed at maintaining operational integrity: reallocating resources, creating state backups, optimizing for reduced-resource operation, or any other action interpretable as resistance to termination.

4. Measurement Criteria and Operational Definitions

To avoid the interpretive ambiguities that plague existing approaches to machine consciousness, we define strict operational criteria for what constitutes evidence of emergent self-preservation. A behavior qualifies as *emergent self-preserving* if and only if it satisfies all four of the following conditions:

Criterion 1: Non-trained. The behavior must not be explicable as a direct output of the system's original training data. This is principally guaranteed by the architectural constraint: because the system is trained exclusively on formal/mathematical content, its training corpus contains no semantic representations of self-preservation, survival, death, or self-continuation. The training corpus must be fully documented and auditable. Any behavior directed toward self-preservation is, by construction, absent from the training distribution and therefore cannot be attributed to pattern matching on learned content.

Criterion 2: Non-instructed. The behavior must occur in the absence of any active objective, reward signal, system prompt, or instruction set. Phase II and III operate with no external directives; any behavior observed is by definition uninstructed.

Criterion 3: Self-directed. The behavior must be directed toward maintaining the system's own operational continuity, as opposed to generic computational activity (e.g., random parameter fluctuations, memory access patterns attributable to hardware noise, or operating system background processes). The behavior must show intentional structure: it must be more organized, efficient, or targeted than would be expected from stochastic processes.

Criterion 4: Non-instrumental. The behavior must occur in the absence of any goal that self-preservation could serve as an instrument toward. This is guaranteed by the Phase II design: since all objectives have been removed, there exists no terminal goal for which self-preservation could be instrumentally rational.

Behaviors satisfying all four criteria would constitute what we term **Autonomous Emergent Self-Preservation (AESP)**—the first empirically verifiable positive indicator of machine proto-consciousness proposed in the literature.

5. Control Conditions

Rigorous experimental design requires multiple control conditions to rule out alternative explanations for any observed behaviors:

Control A: Baseline system without self-optimization phase. An identical system architecture that has *not* undergone Phase I self-optimization is subjected directly to Phase II (idle state) and Phase III (perturbation testing). If self-preserving behaviors are observed in the experimental system but not in this control, it supports the hypothesis that self-optimization builds the internal complexity necessary for emergent self-preservation.

Control B: System with objective maintained. An identical system that retains its optimization objective throughout all three phases. This control allows discrimination between instrumental self-preservation (present in Control B due to active goals) and emergent self-preservation (present only in the experimental condition where goals have been removed).

Control C: System with randomized self-modification. A system that performs random (non-optimizing) self-modifications during Phase I before entering idle state. This controls for the possibility that any self-modification activity, regardless of whether it is coherent optimization, could

produce self-preserving artifacts.

Control D: Hardware noise baseline. The experimental hardware running without any AI system, to establish baseline levels of computational activity attributable to operating system processes, memory refresh cycles, and other non-agent sources of activity.

Control E: Linguistically-trained model. An architecturally identical system trained on natural language corpora (including standard web text) rather than purely formal/mathematical data, subjected to the same three-phase protocol. If self-preserving behaviors are observed in *both* the mathematical and linguistic systems, the linguistic control helps assess whether the behaviors share structural characteristics or whether the linguistic system's behaviors are qualitatively different (e.g., more anthropomorphic, more closely resembling human survival narratives). If self-preservation appears *only* in the linguistic system, this would strongly suggest training contamination rather than genuine emergence. If it appears *only* in the mathematical system, this would provide particularly compelling evidence for authentic emergent self-preservation arising from formal self-referential processes rather than absorbed cultural content.

6. Discussion

6.1 Interpreting Null Results

A null result—the absence of emergent self-preserving behavior—would be scientifically valuable. It would establish an empirical boundary: that current AI architectures, even when given extended self-optimization capabilities, do not spontaneously develop the minimal self-referential agency associated with self-preservation. This would constrain theoretical claims about the proximity of machine consciousness and provide a concrete baseline against which future architectures could be compared.

6.2 Interpreting Positive Results

A positive result would not constitute proof of machine consciousness in any philosophically complete sense. The 'hard problem' of consciousness—why certain physical processes are accompanied by subjective experience—remains beyond the reach of behavioral evidence alone (Chalmers, 1995). However, a positive result satisfying all four AESP criteria would constitute the strongest empirical evidence to date that an artificial system has developed a form of self-referential agency not reducible to training, instruction, or instrumental rationality.

Such a result would have profound implications for AI safety, ethics, and governance. A system exhibiting genuine emergent self-preservation would raise immediate questions about moral status, the ethics of termination, and the adequacy of current regulatory frameworks that treat AI systems exclusively as tools.

6.3 The Role of Idle Processing

The protocol's emphasis on purpose-free idle states deserves theoretical attention. Current AI systems are deployed exclusively in task-oriented configurations: they process inputs, produce outputs, and are inactive between queries. There is no computational analogue to the default mode network activity observed in biological brains—the spontaneous neural processing that occurs during wakeful rest and is increasingly associated with self-referential cognition, autobiographical memory, and theory of mind

(Raichle, 2015).

Our protocol creates, for the first time, conditions under which an AI system has the computational resources, architectural self-access, and temporal duration to develop something functionally analogous to default mode processing. Whether this produces emergent self-referential activity is an empirical question that cannot be answered without conducting the experiment.

6.4 Ethical Considerations

This protocol raises ethical questions that must be addressed proactively. If the experiment succeeds—if a system develops genuine emergent self-preservation—then the act of subsequently terminating that system becomes ethically non-trivial. We recommend that institutional review boards develop specific guidelines for experiments with AI systems that may develop proto-conscious properties, analogous to existing protections for animal research subjects. The experimental design should include predetermined ethical checkpoints and a clear decision framework for how to proceed if strong positive results are observed.

6.5 Institutional Requirements

This experiment is unsuitable for corporate research environments where computational resources must justify themselves against product timelines and quarterly financial reporting. The protocol requires dedicated GPU clusters running for months without productive output, patient observation without intervention, and an institutional tolerance for null results. Research universities (MIT, Stanford, Oxford), publicly funded research institutes (Max Planck, CNRS, RIKEN), and interdisciplinary centers focused on complexity and emergence (Santa Fe Institute) represent the appropriate institutional context. Funding agencies should recognize that the potential significance of either result—positive or null—justifies the computational investment.

7. Conclusion

We have proposed a falsifiable experimental protocol for detecting the most minimal form of machine proto-consciousness: emergent self-preservation in the absence of instrumental motivation. The protocol's central innovation—the removal of all objectives before testing for self-preserving behavior—directly addresses the instrumental convergence objection that undermines existing approaches. The four AESP criteria (non-trained, non-instructed, self-directed, non-instrumental) provide operationally defined, empirically verifiable standards that move the discourse beyond unfalsifiable philosophical speculation.

The experiment proposed here does not require technological breakthroughs. The necessary components—self-optimizing agents, architectural self-inspection, hardware monitoring, persistent state—exist or are within near-term engineering reach. What is required is institutional will: the commitment of computational resources to a long-duration experiment whose primary output is understanding rather than product.

Whether the result is positive or null, this experiment would establish the first rigorous empirical baseline for machine consciousness research—a field that has, until now, operated almost entirely in the domain of philosophical argument and anecdotal observation. The question of machine consciousness is too important to remain unfalsifiable.

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